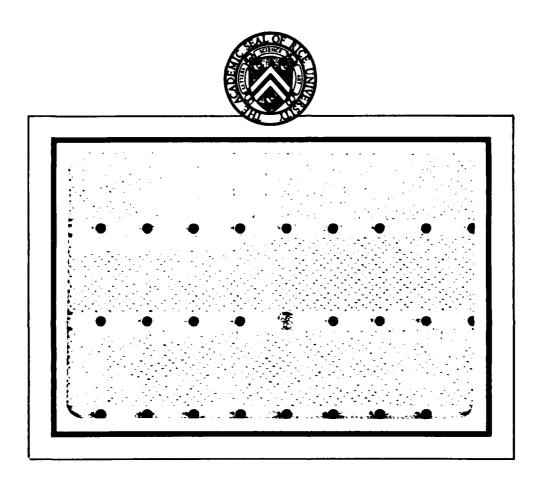


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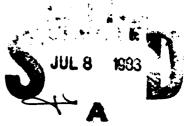


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THE EFFECT OF TASK CHARACTERISTICS ON THE AVAILABILITY HEURISTIC FOR JUDGMENTS UNDER UNCERTAINTY

Gail Fontenelle
Rice University

Technical Report #83-1 May 1983



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THE EFFECT OF TASK CHARACTERISTICS
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FOR JUDGMENTS UNDER UNCERTAINTY

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ABSTRACT

The present study sought to generalize the effect of the availability heuristic to more complex tasks and across various task categories. The experimental design involved the manipulation of event characteristics in order to induce a heuristic processing strategy for designated available events. The effect of these manipulations was investigated for three types of response measures and across a range of event frequencies. Results demonstrated the generalizability of the availability heuristic across complex tasks and three types of response measures--frequency estimation, probability estimation, and choice predictions. The availability of an event in memory produced an overestimation of the frequency and probability of event occurrences. Similarly, choice predictions judged available events as more likely to occur. However, this effect was not consistent across all levels of assigned event frequencies. The present study extended the generalizability of the availability heuristic to more complex tasks and provided an exploratory step toward defining the degree to which basic findings hold across a range of task characteristics,

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INTRODUCTION

General Background

Decision theory in the 1950s and 1960s was based on the assumption that individual decision makers operate in accordance with axiomatic models of optimality (Edwards, 1961). Research within this framework was aimed at investigating the extent to which actual decision behavior conformed to normative principles (Edwards & Tversky, 1967); deviations from these principles were attributed to the limited information processing capacity of decision makers (Edwards, 1968).

In 1967 Peterson and Beach adopted this viewpoint in their development of a theory about human behavior in uncertain situations describing human beings as "intuitive statisticians." Their conceptualization is consistent with data showing that the relationship between estimated and actual frequency is described well by the identify function. Howell's (1973) review of this literature concluded that "... subjects show a remarkable facility for synthesizing and storing the repetitive attribute of event occurrences" (p. 51). Similarly, Estes (1976) observed that subjects in probability-learning experiments were extremely efficient at acquiring relative frequency information.

Except for a few isolated studies (Attneave, 1953; Hintzman, 1969; Tiegen, 1973; Underwood, 1969; Underwood, Zimmerman, & Freund, 1971), research on judgments under uncertainty was dominated by the normative approach until the publication of a series of innovative and influential articles by Tversky and Kahneman (1971, 1972, 1973, 1974). Tversky and Kahneman's work demonstrated that people often employ "heuristic"

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processing strategies--simplified rules of thumb--to arrive at judgments under uncertainty. These rules of thumb violated normative standards and contrasted sharply with the conception of man as an intuitive statistician.

Although the present study is concerned specifically with the availability heuristic, it might be well to begin with a brief review of several heuristics demonstrated by Kahneman and Tversky. The review is intended to familiarize the reader with the concept of "heuristic" processing strategies and to illustrate their pervasiveness in judgments made under uncertainty.

In a series of articles, Tversky and Kahneman demonstrated three

Heuristic Strategies in Judgments Under Uncertainty

heuristics employed in making judgments under uncertainty:

(a) representativeness, (b) availability, and (c) adjustment from an anchor. For example, Kahneman and Tversky (1972) described several situations in which people judge the probability that an object or event belongs to a class or process by how similar or "representative" it seems to be of other objects or products of that class. This approach to the judgment of probability can lead to serious errors because representativeness is not influenced by several factors that should affect judgment of probability. For example, prior probability of outcomes and sample size are typically ignored by people using the representative heuristic.

Two hypotheses incorporate the concept of representativeness:

(a) People expect even small samples to be highly similar to their parent population and also to represent the randomness of the sampling process (Tversky & Kahneman, 1971, 1974) and (b) people often rely on

a Tversky, 1972). These two hypotheses can explain (a) the common belief that chance processes are self-correcting, (b) the exaggerated faith in the stability of results observed in small samples, (c) the gambler's fallacy, (d) the common tendency to exaggerate the consistency and predictive value of personality traits, and (e) the tendency to overestimate the correlation between similar variables (Tversky & Kahneman, 1982).

In other cases decision makers were found to rely on an event's availability in memory to index its frequency of past occurrence or its probability of present occurrence (Tversky & Kahneman, 1974).

Availability is a useful clue for assessing frequency or probability because instances of large classes are usually recalled better and faster than instances of less frequent classes. However, availability is affected by factors other than frequency or probability such as (a) the salience or differential retrievability of certain events, (b) the effectiveness of a search set, (c) the imaginability or availability of construction of an event, and (d) the illusory correlation effect—the overestimation of the co-occurrence of two events that have strong associative bonds.

And finally, Tversky and Kahneman (1974) discussed the failure of decision makers to make necessary adjustments of initial judgments. It was demonstrated that starting points yield estimates biased toward these initial values. This "anchoring" effect is due to

(a) insufficient adjustment, (b) the tendency to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events, and (c) anchoring in the assessment of subjective

probability estimation—the degree of adjustment depends on the procedure of elicitation.

The fact that actual decision behavior is often inconsistent with normative standards underscores the importance of the distinction between how the decision maker ought to behave and how he or she does behave. As noted in a review by Slovic, Fischhoff, and Lichtenstein (1977), the shift from a normative model to a descriptive model typified by Tversky and Kahneman's work was an important change and provided new direction for research in the area.

The same review by Slovic et al. (1977) described a long list of judgmental biases, deficiencies, and cognitive illusions that had been demonstrated in the judgment of uncertainty. Four years later Einhorn and Hogarth (1981) noted that the list had increased in size and captured the interest of researchers in other areas in psychology (Nisbett & Ross, 1980; Rowe & Rose, 1977) as well as such diverse disciplines as sociology, law, and risk management (e.g., Miller, 1980; Pennington, 1981; Saks & Kidd, 1979; Slovic, Kunreuther, & White, 1974). Einhorn and Hogarth proposed that now researchers must go beyond cataloging the types of heuristic biases and begin considering the specific conditions under which heuristic biases occur.

One fruitful direction for future research on the heuristics may be the investigation of specific task conditions and characteristics.

Several researchers have suggested that seemingly minor changes in task characteristics may determine whether or not people use heuristics (Ebbeson & Konecni, 1980; Hammond, McCelland, & Mumpower, 1980; Howell & Burnett, 1978). The generalizability of the effect of heuristic strategies may be dependent on how tasks vary between the laboratory and

the natural environment and what kinds of effects can be expected from such differences.

The present study investigated the generalizability of a heuristic processing strategy—specifically, the availability heuristic—across more complex tasks and various task categories. Although researchers have invoked the availability heuristic as an explanation since its conception 10 years ago, the majority of the studies designed to demonstrate the heuristic have employed experimental stimuli lacking in the multidimensionality that characterizes repetitive events in the real world. Even studies that employed "real world" events as stimulus materials were not designed to allow subjects to actually experience the data. Because there is rarely any uncertainty in most laboratory studies about what information should be attended to or how it should be encoded, highly simplistic stimuli may not yield simplified representations of real world heuristic processing but qualitatively different representations.

The present study attempted to generalize the effect of the availability heuristic to more complex tasks that simulate the multidimensionality that characterizes repetitive events in the real world. In addition, the study investigated the role that seemingly minor task characteristics play in amplifying or reducing heuristic bias.

First, a review of the availability heuristic is presented to familiarize the reader with Tversky and Kahneman's original conceptualization and to discuss the contributions made by research in both the frequency estimation and social judgment literature. Following this discussion examples of recent results evidencing the sensitivity of

judgment to seemingly minor changes in tasks are presented in order to illustrate the importance of investigating the effect of such variables on the availability heuristic for judgments under uncertainty.

The Availability Heuristic

Tversky and Kahneman's Conceptualization of the Availability Heuristic

Of the heuristics discussed by Tversky and Kahneman (1974), the availability heuristic is hypothesized to be the most frequently used. Availability is a useful clue for assessing frequency or probability because instances of large classes are usually recalled better and faster than instances of less frequent classes. However, the heuristic is often a fallible guide for such judgments because many factors besides actual frequency or statistical probability affect the availability of events in memory. Though availability is often an appropriate cue for such judgments, it is also affected by subtle factors unrelated to likelihood. For example, individuals who have been involved in a recent car accident may experience a temporary rise in the subjective probability of an accident. One may assess the divorce rate in a given community by recalling divorces among one's acquaintances. According to Tversky and Kahneman (1973, 1974, 1982), reliance on the availability of an event in memory may lead to systematic overestimation for familiar, emotionally salient, or otherwise imaginable events.

The positive impact of extraordinary characteristics on recall and recognition is also well-documented in the basic memory literature, where it is often referred to as the "Von Restorf Effect" (Crowder, 1976). For example, Radtke, Jacoby, and Goedel (1971) found that inclusion of such nonsemantic features such as underlining target words enhanced retrieval. Whitlow and Skaar (1979) reported that target

events which occurred with high numerosity (e.g., the number of independent occurrences of an event within a discrete temporal period) were judged to be more frequent than events which had actually occurred with greater total frequency but relatively low numerosity. Virtually any sort of distinguishing characteristic will serve to increase the probability of its retrieval. However, Tversky and Kahneman were the first to propose that such mediating variables also operate in real-world or highly complex situations involving judgments of frequency and probability.

Tversky and Kahneman (1973) presented a series of 10 studies which demonstrated that people can assess availability of instances with reasonable speed and accuracy and that the judged frequency of classes is biased by the availability of instances for construction and retrieval. For example, subjects were instructed to estimate the relative frequency with which the letter \underline{R} appeared in the first and third position in words of the English language. The majority of subjects judged \underline{R} to be more frequent in the first than in the third position despite the fact that \underline{R} occurs more frequently in the third position. Tversky and Kahneman proposed that people answer such a question by assessing the ease with which instances of the two categories come to mind. Since it was easier to think of words that start with an \underline{R} than of words where \underline{R} is in the third position, the first category of words was judged to be more frequent.

The Availability Heuristic in the Frequency Estimation Literature

Following the publication of Tversky and Kahneman's paper, other researchers in the area of frequency estimation began to examine their findings in light of the availability heuristic. For example, Rowe and

Rose (1977) employed the availability heuristic to explain their finding that frequency estimations for target items in word lists were higher when subjects were required to rate the imagery of all list items as they were presented. However, only a few studies (Beyth-Marom & Fischhoff, 1977; Lichtenstein, Slovic, Fischhoff, Layman, & Combs, 1978) in the frequency estimation literature investigated the connection between the availability heuristic and cognitive processes directly. Beyth-Marom and Fischhoff (1977) asked subjects to make both aided and unaided estimates of category size for countries and kibbutzim, the names of which began with three different letters. In the aided estimate condition, subjects were asked to list as many instances of countries and kibbutzim as possible beginning with one of the three letters prior to their category estimations. For instances that were easily available (e.g., subjects were able to produce many examples of countries), unaided estimates of category size were correlated with two direct measures of availability: time to produce first instance and number of instances produced in the first five seconds. For instances that were not easily available (e.g., subjects were unable to produce many examples for kibbutzim), direct measures of availability did not correlate with unaided estimation. However, aided estimates of easily available instances did not correlate perfectly with total production of instances, while unaided estimates of less available instances correlated with actual category size. The authors concluded that factors other than ease of instance production (e.g., lexicographic structure of the language) had influenced frequency estimates and that these factors may prove to be highly situation specific. Unfortunately,

the actual correlations were not reported and therefore it is difficult to evaluate these conclusions.

A paper by Lichtenstein et al. (1978) is another that closely examines the availability heuristic in frequency estimation. In a series of three studies, subjects assessed the frequencies of causes of death by making direct estimates and paired comparisons. Despite the findings that (a) frequency estimates for causes of death generally increased with increases in true frequency and (b) discriminability of causes increased with the ratio of their statistical frequencies, the overall accuracy of both direct estimates and paired comparisons were quite poor. Two kinds of systematic bias were identified: (a) a tendency to overestimate small frequencies and underestimate large frequencies, and (b) a tendency to exaggerate the frequency of some specific causes and to underestimate the frequencies of others, at any given level of objective frequency.

The former bias is well-documented in the research on frequency and probability estimation (Attneave, 1953; Erlick, 1964; Stevens & Galanter, 1957; Teigen, 1973). Previous researchers have suggested that a tendency to avoid extremely high or low responses (Erlick, 1964), anchoring (Attneave, 1953), and range effects (Steve & Galanter, 1957) may account for this bias. Lichtenstein et al. suggested both anchoring (Lichtenstein & Slovic, 1971; Tversky & Kahneman, 1974) and the availability heuristic as possible explanations.

However, it is the results and discussion related to the latter bias--the tendency to exaggerate the frequency of some specific causes and to underestimate the frequency of others--that provided valuable clarification of the availability heuristic. In a fourth experiment,

Lichtenstein et al. examined people's direct and indirect experiences (e.g., personal experience, newspaper coverage) with those specific events for which relative frequency was consistently misjudged.

Lichtenstein et al. determined that measures tapping the availability of information about causes of death did an excellent job predicting subjects' judgments of the frequencies and relative frequencies of these causes. The authors employed the concept of availability to explain that it was the "sensational" causes of death such as botulism, tornado, flood, and homicide that were overestimated (relative to predictions based on the regression model), while the undramatic, quiet killers such as asthma, tuberculosis, or diabetes were underestimated.

Lichtenstein et al. made two significant contributions to the literature on the availability heuristic: (a) The researchers employed real world events as stimuli for which actual frequency standards exist and (b) their analyses of potential sources of bias contributed to the strength of the argument that vividness or sensationalism is an important explanation for the availability heuristic. However, Shanteau (1978) argued that their findings are not "empirically compelling" due to the fact that subjects were not exposed to the actual stimuli which were used as standards for comparison. Also, he suggested that the interpretations of the data would be more convincing if the same results were replicated for other types of stimuli. There is clearly a need for further research on the effect of the availability heuristic in judgment of uncertainty.

The Availability Heuristic in the Social Judgment Literature

The theoretical implications of Tversky and Kahneman's work on the role of the availability heuristic in judgment of uncertain events has also influenced the work on social judgment (see Nisbett & Ross, 1980; Taylor, 1982; Taylor & Thompson, 1982 for reviews). Considerable effort has been devoted to the development of theory concerning the mechanisms and cognitive processes underlying the availability heuristic in social judgments of uncertainty. Unfortunately, although the availability heuristic has been raised often as one possible explanation for difficult social phenomena, there is lack of direct empirical evidence. The unique contribution made by the work in social judgment has been the refinement of concepts vital to the successful manipulation of availability. Two works in particular have contributed to this refinement process, Nisbett and Ross (1980) and Taylor and Thompson (1982).

An influential book by Nisbett and Ross (1980) reviewed the many explanations of the availability bias and proposed the vividness hypothesis as the most important. They stated that "... information may be described as vivid, that is, as likely to attract and hold our attention and to excite the imagination to the extent that it is (a) emotionally interesting, (b) concrete and imagery provoking, and (c) proximate in a sensory, temporal, or spatial way" (p. 45). They proposed that the more vivid the information, the more likely it is to be recalled and hence disproportionately available for influencing inferences at any time after information is initially encountered. The inferential impact of vividness could occur immediately upon receiving information or after a delay. The authors identified three possible

cognitive processes that could account for the effect: (a) the greater likelihood that more vivid information provides a larger quantity of information that receives more attention during encoding, (b) the greater likelihood that vivid information recruits additional information of similar import from memory, and (c) the greater likelihood that more vivid information is pondered and rehearsed to a greater extent in memory.

A recent review by Taylor and Thompson (1982) focused on studies testing the vividness hypothesis. They concluded that the vividness effect had produced discrepant results; however, not all researchers in the area share this conclusion (Anderson, 1983). The majority of the studies have utilized persuasive communications as stimulus objects and attitudes and opinions as judgments. Despite these similarities, operationalizations of vividness have differed substantially. Researchers have used concrete language, pictures, videotapes, direct experience, and case histories. Overall, the manipulations have failed to produce a reliable differential recall effect. Even when recall differences were demonstrated, they did not predict attitudes or opinions consistently. Studies examining the use of case histories produced the most favorable results. Case histories affected attitudes more strongly than statistical or base rate information. However, Taylor and Thompson concluded that explanations other than the vividness hypothesis could account for the greater impact of case histories on attitudes. They suggested that (a) the failure to maintain information equivalency across conditions and/or (b) the underuse of statistical information rather than the overuse of case history information might explain the effect.

Taylor and Thompson (1982) presented an alternative hypothesis of salience or differential attention as an explanation for the failure of the laboratory studies and the lack of support for the vividness hypothesis proposed by Nisbett and Ross. Differential attention refers to the phenomenon in which one's attention is differentially directed to one portion of the environment rather than another and operates via differential encoding of information. However, except for emphasizing the importance of differential attention versus absolute attention, Taylor and Thompson's differential attention hypothesis is difficult to distinguish from Nisbett and Ross' argument for the vividness effect via encoding processes. Whether the encoding process alone is necessary and sufficient to account for all instances of the availability heuristic remains to be demonstrated.

Regardless, the work in social judgment has made a unique contribution to the literature on the availability heuristic. It provides an initial starting point from which to explore various operationalizations of availability. The theoretical work of Nisbett

and Ross (1980) and Taylor and Thompson (1982) refined concepts which are vital to the successful manipulation of availability.

Generalizing the Effect of the Availability Heuristic Across Tasks and Task Characteristics

Importance of Task Characteristics

Among the more significant insights that have emerged over the last few years in decision theory is the important role played by seemingly minor task characteristics in the way individuals approach decision problems (Hammond et al., 1980; Howell & Burnett, 1978; Tversky & Kahneman, 1981; Howell, Note 1). Some task characteristics may induce or amplify distortions in human processing; others may promote more "optimal" strategies. For example, Hammond and his associates (Hammond, 1981; Hammond, McCelland, & Mumpower, 1978, 1980) argued that task characteristics may induce the individual to use different strategies in processing information.

Some support for this position can be found in policy-capturing studies that attempt to model the behavior of the individual decision maker. For example, Slovic and MacPhillamy (1974) demonstrated that variation in cue characteristic such as their dimensions (e.g., percentile scores relative to T-scores) may affect cue utilization and consequent judgment.

Another group of studies that highlighted the importance of task characteristics in decision making are those that compare judgments made in real world tasks to those made in a laboratory simulation of the same task. For example, Phelps and Shanteau (1978) reported that livestock judges took many more cues into account in their judgments of swine when the cues were presented in decomposed form using a fully crossed design

than when pictures of swine, rather than feature lists, were evaluated. In one of several examples presented by Ebbesen and Konecni (1980), actual bail-setting decisions were compared with decisions made by the same county judges for a simulated bail-setting task. Multiple regression analyses indicated that the same four factors that were manipulated in simulation also accounted for 95% of the variance in the actual bail decisions. However, the pattern of results for the simulated and naturalistic data were quite different. The extent to which the accused was tied to the local area (e.g., owned a home, was employed, and was married) was the most important factor that emerged from the simulated task. In contrast, analysis of the decisions in the actual bail hearings suggested that judges were primarily influenced by the district attorney's recommendation and that the local ties factor was negatively correlated with the judges' decisions.

Ebbesen and Konecni (1980) summarized recent findings in the area, concluding that what remains is "... a simple descriptive statement suggesting that decision makers are sometimes sensitive to task characteristics that are not specified by prior normative or theoretical considerations (Olson, 1976) and that researchers do not know when oversensitivities will emerge" (p. 24). They proposed that people continually shift their strategies to meet the demands of the task and that decision rules are created to fit the task. In this view, features of the decision task and measurement procedures that have little or no theoretical relevance might be expected to determine at least part of the results one observes, e.g., the context in which the decision is presented, the salience of alternatives, the concreteness of the information, the order of the presentation, the similarity of the cues,

the nature of the decomposition of the task, and the form of the measure.

An obvious first step toward understanding the relationship between task characteristics and resulting decisions is the identification and classification of relevant task components. Recently several attempts were made to develop a taxonomy of task characteristics (Hammond et al., 1980; Howell & Burnett, 1978; Tversky & Kahneman, 1981). Howell and Burnett (1978) have developed a promising approach to the classification of task features that is concerned specifically with judgments of uncertainty.

A Cognitive Taxonomy for Uncertainty Measurement

Howell and Burnett (1980) highlighted the importance of the interaction between the decision maker and the task in shaping decision behavior. They proposed that the decision maker has a variety of information processing options or strategies in his repertoire, but which one he invokes in a particular case may depend on the task structure. Therefore, a promising approach to classification would focus on the cognitive implications of task features. Basically, they attempted to distinguish some key task parameters in terms of presumed links with underlying cognitive processes.

The basic tenets of Howell and Burnett's argument are as follows.

Judgments under uncertainty derive from combinations of four principal classes of cognitive processes: prior generator knowledge, stored historical data (usually event frequency), heuristics, and systematic bias. A combination of characteristics of the task and stimulus events determines which of these processing options is invoked. Four distinct response requirements constituted the basic task demands: frequency

estimation, probability estimation, prediction, and choice. These together with characteristics of events--frequentistic versus nonfrequentistic, internal versus external source of control, and known versus unknown generators--were used as the primary taxonomic parameters. Howell and Burnett concluded that uncertainty judgments could be predicted on the basis of the above defining task features and the possible processing option they induce.

A foremost objective of this taxonomy was to unravel possible conceptual differences among what are commonly regarded as equivalent measures of uncertainty. Such diverse measures as direct numerical judgments and various choice paradigms have been used to measure uncertainty. Howell and Burnett proposed that such seemingly minor variations in response measures directly affected judgments under uncertainty. For example, Howell's (1972) subjects judged their own performance on a skill task with greater confidence when a choice measure was used than when probability estimates were obtained. Such methodbound results severely limit the generalizability of any conclusions drawn about judgments under uncertainty.

The Effect of Response Type on Judgment Under Uncertainty

The hypothesis derived from the taxonomy, that the impression of uncertainty is directly related to the response required of the subject, was tested in a study by Howell and Kerkar (1982). The basic research plan was to develop subjects' impressions of the stochastic properties of a variety of kinds of observed events and then probe those impressions using different response requirements. The task consisted of a simulated resource-allocation problem in which the subject served as a dispatcher of coordinated emergency services. Performing this

function over a number of sessions served to establish the impressions of event likelihood upon which he was subsequently required to act in different response modes. The three types of indicator responses were frequency estimation, probability estimation, and predictive choice. Based on the logic developed by Howell and Burnett (1978), it was proposed that all three responses would reflect stored impressions of observed event frequencies but that frequency estimates would produce a more veridical account than probability estimates.

The results of Experiment I confirmed the hypothesis. The authors found that in a frequentistic task, uncertainty was judged more accurately using a past-oriented frequency estimation than a future-oriented probability estimation. Experiment I also tested the effect of the estimation tasks on subsequent predictive choice performance. The predictive choice task required the subjects to indicate which one of a pair of presented events was most likely to occur. The data clearly indicated that the estimation groups (frequency and probability) made more accurate choices than a control group (which was similar to the other two groups in all respects except that it made neither type of estimation). Experiments II and III sought to clarify the process by which estimation enhances choice performance. Results were explained best in terms of a cueing hypothesis. Accuracy of prediction choices was enhanced by both types of estimation (frequency and probability). The authors interpreted these results as follows: requiring the subject to estimate before choice performance cued retrieval of the frequency component of both the frequency and probability estimate. They concluded that, were the estimate itself (i.e., the recorded uncertainty value) the key item of information, the

choices would have corresponded more reliably with the quality of the estimates (i.e., the superior accuracy of frequency estimates over probability estimates).

The Effect of Response Type on the Availability Heuristic for Judgments of Uncertainty

The basic research plan of the present study borrowed heavily from the theoretical work by Howell and Burnett (1978) and the empirical work by Howell and Kerkar (1982). The study extended the work of Howell and Kerkar by attempting to induce a heuristic processing strategy. The logic in this approach is that if heuristic processing is indeed a function of task conditions, then it should be possible to shift judgment along the normative-heuristic dimension by manipulating event characteristics. The results of these manipulations should be predictable change in the measurement of judgments under uncertainty. However, the degree to which the changes produced by a heuristic processing strategy are evidenced may depend on the type of response measure. Due to the fact that the underlying cognitive processes by which the availability heuristic operates have not been delineated it was impossible to make specific predictions regarding the degree to which the different response measures would reflect the induced heuristic bias.

The basic task employed by Howell and Kerkar (1982) was also adopted for use in the present study for two reasons: (a) It facilitated a direct comparison of results from the present study with those of Howell and Kerkar and (b) the key features of the task defined it as a multidimensional task that closely simulated repetitive events in the real world. If the availability heuristic could be successfully

induced and shown to affect judgments of uncertainty, the effect of availability could be generalized to more complex tasks.

To recapitulate, the purpose of the study was twofold: (a) to generalize the effect of the availability heuristic to more complex tasks and (b) to investigate the role that seemingly minor task characteristics play in amplifying or reducing heuristic bias.

METHOD

Task

The task scenario used to expose subjects to a complex array of event frequencies was that of emergency dispatcher for a hypothetical city. The sole purpose of the task scenario was to provide structured tasks that allowed subjects to acquire impressions of event frequency and probability through experience. The acquisition phase of the experiment occurred over three sessions. In each session subjects completed (a) a resource allocation task and (b) a dispatching/verifying task. Upon completing the third session of the acquisition phase, subjects performed an estimation and a predictive choice task. Immediately following the third session subjects provided either the frequency of specific events or the probability that the event would occur on future occasions. After the estimation task, subjects were presented with a series of pairs of events and asked to indicate which they would choose as more likely to occur next.

Task Scenario (Acquisition)

Subjects served individually in the role of dispatcher of emergency services for a hypothetical city. Their task was to dispatch emergency vehicles to nine precincts of that city in response to programmed emergency calls. The nine precincts were displayed graphically as a nine-block grid on the screen of a TRS-80 microcomputer. Each emergency call was a request for an ambulance or police vehicle, and each call represented either an actual emergency or a false alarm. Each call was displayed in the grid block corresponding to the precinct in which it

occurred. The word "Police" or "Ambulance" was displayed, followed by the precinct number. "Police-8" represents an example of an event display.

Each type of emergency (police or ambulance) in each precinct constituted a unique event. There were 18 events, that is, two types of emergency calls in each of the nine precincts. These 18 events were identified by the type of call, police (P) or ambulance (A), and the precinct in which it occurred (1 through 9). Frequencies of 0, 1, 2, 4, 8, and 10 were randomly assigned to the 18 events, and the distribution is given in Table 1. There were a total of 225 events, which were presented in random order during three sessions. The stochastic process by which the events were generated remained stationary from session to session in all conditions. Subjects could thereby acquire experience with the overall pattern of event uncertainties over sessions but, due to the complexity of the situation and the absence of specific information concerning how events are generated, they would not be expected to master the entire task.

At the beginning of each session, subjects performed a resource allocation task. Subjects distributed a fixed number of vehicles, 50 police and 30 ambulance, among the nine precincts at the beginning of each session in what they considered to be the most advantageous fashion for later allocation to particular emergencies. These allocations for each precinct were displayed on the screen in the appropriate location. Then the emergency calls appeared one at a time. The subjects' task was to respond appropriately to each of the incoming calls. Immediate feedback was given as to whether the call was a true emergency or false alarm.

TABLE 1
ASSIGNMENT OF FREQUENCIES TO THE 18 EVENTS

Frequency Distribution		Events		
Per Session	Over Three <u>Sessions</u>	Police (P)	Ambulance (A)	
0	0	Р3	A7, A8	
1	3	P6*	A2, A5	
2	6	P2	A1, A3	
4	12	P4, P9	A9*	
8	24	P1, P7	A6	
10	30	P5, P8	A4*	

^{*}These three events were manipulated as available events. All other events served as control events.

A cost/payoff scheme was devised which took into account both the availability of emergency vehicles and the appropriateness of the decision to dispatch or verify (see Table 2). A score was computed that reflected the quality of each decision. The score was displayed continuously and accumulated over each session. Overall performance indicated by the cumulative score over three sessions was of little concern. Task performance was scored in order to motivate subjects to attend to a variety of different frequentistic events.

The task scenario was developed by Howell and Kerkar (1982). They described the key defining features as (a) a frequentistic event base--items to be processed occurred repeatedly, (b) complexity and form of presentation designed to insure a relatively cognitive approach, (3) plausibility or face validity--subjects had reason to see the task as inherently meaningful, and (4) incidental status of uncertainty task--dispatching permitted but did not emphasize the formation of uncertainty impressions of the stochastic properties of a variety of observed events.

Estimation Task

At the end of the third session, subjects provided frequency and probability estimates concerning the 18 events in accordance with their particular group assignment. The frequency estimation questionnaire asked subjects to estimate how many times each of the 18 events had appeared. The probability estimation questionnaire asked each subject to estimate the chances (0-100%) that the next call which would appear would be one of the 18 events (see Appendix A).

TABLE 2
POINT SYSTEM

	<u>Vehicles Available</u>		Vehicles Not Available	
	True Emergency	False Alarm	True Emergency	False Alarm
Dispatch	1	-1	-1	-2
Verify	-1	1	-2	0

Predictive Choice Task

Following the estimation task, subjects performed the predictive choice task. All subjects were presented with a list of 33 predictive choice pairs and instructed to circle the event in each pair which was more likely to occur (see Appendix A).

Subjects

Thirty-two volunteers from several undergraduate psychology courses served in exchange for course credit. They were assigned randomly to two conditions that were distinguished on the basis of response mode. Sixteen subjects made frequency estimates (FE) and 16 subjects made probability estimates (PE). All subjects made predictive choices.

Design

The basic design was a 2 (frequency estimation versus probability estimation) x 2 (available events versus control events) x 3 (three event occurrences versus twelve event occurrences versus thirty event occurrences). The availability of events and number of occurrences variables were designed as within-subject manipulations.

Availability Manipulation

The presentation of designated events was manipulated in two ways in order to make them more available in memory. First, the display of the event on the TRS-80 screen, for example "Police-6," would blink on and off for eight seconds every time the event category occurred. All other events were presented as a constant display.

Secondly, subjects were instructed that the blinking of the event display would indicate that additional information was received on this particular emergency call. It was explained that in many instances more than one citizen or city official present at the scene of an emergency

call would call in additional information to the dispatcher. This additional information was presented on 5 x 8 index cards (see Appendix B for examples). Each card represented the transcript of a "telephone call" reporting emergencies. Each card was identified by the precinct number and brief description of the primary land use of that precinct, for example, "A4--residential low income." The case histories were constructed from actual emergency calls received at the Central Alarm Unit of the City of Houston, Texas, Fire Department. The order of presentation of the case histories was identical across all subjects. The cards were ordered such that their occurrences in the stack of cards corresponded to the order in which the events were presented on the screen. Subjects were instructed to flip the card over after they had read the case history and before they responded to the call. Also, they were told that they would be asked to recall the case histories at the end of the experiment. This instruction was designed to insure that subjects read the case histories.

Three out of 18 events were manipulated as <u>available</u> events, P6, A9, and A4. Each of these events occurred at a different assigned frequency: P6--3, A9--12, and A4--30 (see Table 1). In total, 45 out of 225 events were manipulated as available events. Events which occurred at the same assigned frequency as the three available event types but whose presentations were not manipulated served as <u>control</u> events. All subjects viewed both available and control events.

Each of the events designated as available occurred at a different assigned frequency throughout the three sessions (see Table 1). The three different levels of occurrence were 3, 12, and 30 times across all

sessions or 1, 4, and 10 times within each session. This variable was also manipulated as a within-subject variable.

Procedure

The experiment was carried out over two days. Instructions were given prior to the first session and included an explanation of the purpose of the research ("to gain a better understanding of how people make resource-allocation decisions"), procedural instructions, and familiarization trials. Specific instructions for the estimation and choice of tasks were given at the end of the third session.

The subject was seated in a small experimental booth before a TRS-80 microcomputer, on the screen of which was displayed: (a) a map of the city zones, (b) a cumulative score for the session, (c) an indication of available resources, (d) each emergency call as it appeared, (e) the response to each call as it occurred, and (f) immediate feedback on the outcome of each response. The distribution and sequencing of the 75 events comprising each session was programmed (see Table 1 for the assignment of frequencies to events). Subjects entered their responses to the calls using the computer keyboard, and the display of each call remained on the screen until the response was properly entered. Thus, the input sequence was largely self-paced (limited only by machine speed).

Each session consisted of the resource allocation task followed by the dispatching task. Subjects responded to 75 calls in each of the three sessions. On the first day subjects completed two sessions. On the second consecutive day subjects completed a third session. At the end of the third session, the \underline{PE} and \underline{FE} questionnaires were administered to their respective groups. Items probed the uncertainty associated

with specific event categories (see Appendix A). Following these estimations, the 33 predictive-choice pairs were presented (see Appendix A).

RESULTS

Estimates

Frequency estimates were converted to proportions by dividing the raw score by the total number of events so they would be on the same scale as the probability estimates. The quality of the estimates was evaluated in two ways. Since the stationary stochastic process used to generate the repetitive events was identical in each session, there was in all cases a basis for an objective definition of frequency and probability of events. Performance was described in terms of deviation from this objective referent. The deviations were expressed as absolute signed error or calibration (estimate - objective referent), relative error (estimate/objective referent), and relative error using the subjects' estimation of the total number of events to adjust the estimates (adjusted estimate/objective referent). In addition, the latter two sets of data were subjected to a log transformation. Since the results were similar for all forms of the data, statistical analyses performed on relative error calculated with the adjusted estimate will be presented unless otherwise stated (see Appendix C for figures and Appendix D for analysis of variance tables).

As predicted, available events were judged to have occurred more often than control events (\underline{M} = 1.93 and \underline{M} = 1.53, respectively). However, as can be seen in Figure 1, this finding was not consistent across all three frequency levels. For events that occurred 3 times out of 225, available events (\underline{M} = 3.93) were judged to have occurred more often than control events (\underline{M} = 2.83). Also for events that occurred 30

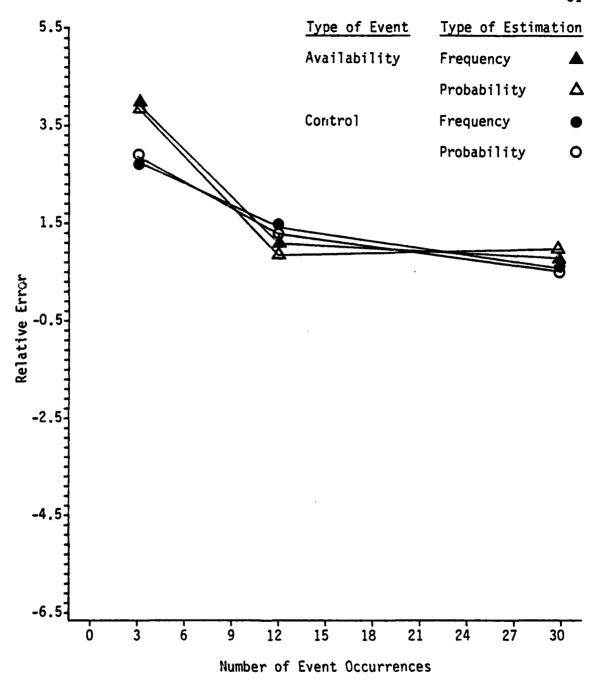


FIGURE 1

RELATIVE ERROR CALCULATED WITH THE ADJUSTED ESTIMATE
FOR FREQUENCY AND PROBABILITY ESTIMATION PERFORMANCE
FOR TYPE OF EVENT (AVAILABILITY VERSUS CONTROL)
AND LEVEL OF EVENT OCCURRENCE (3 VERSUS 12 VERSUS 30)

times out of 225, the available events (\underline{M} = -.89) were judged to have occurred more often than the control events (\underline{M} = -.57). However, for the events category that occurred 12 times out of 225, the control events (\underline{M} = 1.35) were judged to have occurred slightly more often than the available events (\underline{M} = -.97).

The absence of an availability effect at this assigned frequency level was unexpected. However, consideration of the overall pattern of estimation of both available and control events provides some explanation. In general, subjects overestimated events that occurred 3 times out of 225 ($\underline{M} = 3.38$) and underestimated events that occurred 30 times out of 225 ($\underline{M} = -.73$). However, events that occurred 12 times out of 225 ($\underline{M} = 1.16$) were judged fairly accurately.

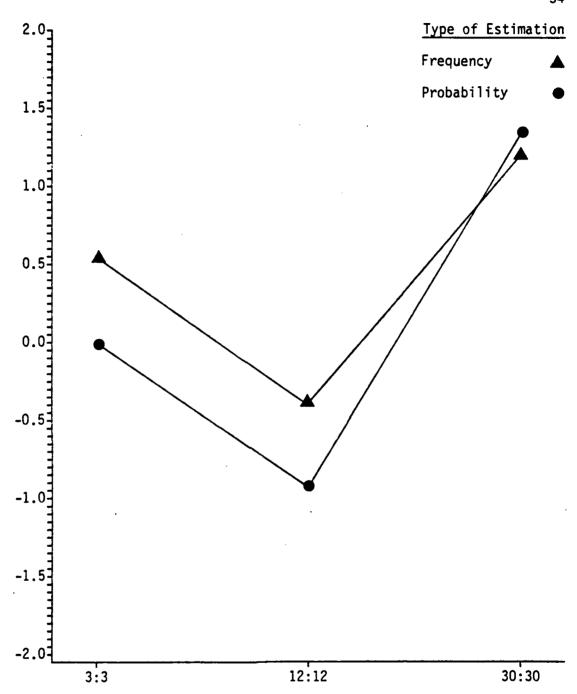
Statistical analyses support these conclusions (see Appendix D for analysis of variance tables). A two-way interaction of type of event (available versus control) by number of occurrences (3 versus 12 versus 30) was significant for all cases: \underline{F} (2, 60) = 17.51, \underline{p} = .000 for calibration and \underline{F} (2, 60) = 12.23, \underline{p} = .000 for relative error. The main effect for type of event was significant. The \underline{F} (2, 60) values were 6.20, \underline{p} = .019 for calibration and 9.69, \underline{p} = .004 for relative error. Also the main effect for number of occurrences was significant. The \underline{F} (2, 60) values were 301.9, \underline{p} = .000 for calibration and 214.18, \underline{p} = .000 for relative error.

There were no significant differences for frequency estimates $(\underline{M}=.31)$ compared with probability estimates $(\underline{M}=.25)$ nor any significant interactions of type of estimation with any other variable. The average correlations of frequency and probability estimates with the objective referent for subjects were .60 and .56, respectively. After

converting these \underline{r} 's to \underline{F}_z , there was no significant difference in accuracy for type of estimation.

Predictive Choice Pairs

To examine the effect of the type of event (availability versus control) and the ratio of occurrences, available events were paired with control events of identical frequencies, that is, 3:3, 12:12, 30:30. If the subject indicated the available event to be more likely to occur, the choice was coded +1. If the subject indicated the control event as more likely, the choice was coded -1. As predicted, the effect of type of event was indicated by the positive direction of the grand mean (M = .2889). Across all levels of ratio of occurrences subjects chose the available event as more likely to occur, \underline{F} (1, 28) = 4.41, \underline{p} = .04. However, as can be seen in Figure 2, this finding was not consistent across all three levels of assigned frequency. For choice pairs constructed with the available event which occurred 12 times and a control event which occurred 12 times, subjects tended to choose the control event as more likely to occur (M = -.6667). For choice pairs constructed of available and control events which occurred 3 and 30 times, subjects chose the available event as more likely to occur (M = .2667 and M = 1.2667, respectively). The effect of the ratio of occurrences variable was significant, \underline{F} (2, 56) = 12.24, \underline{p} = .000. There was no significant difference in choice performance following frequency estimation (M = .444) compared with choice performance following probability estimation ($\underline{M} = .133$) nor any significant interactions of prior type of estimation with any other variable. (See Appendix D for analysis of variance table.)



Ratios of Event Occurrence

FIGURE 2

PREDICTIVE CHOICE PERFORMANCE FOR CHOICE PAIRS
COMPARING AVAILABLE AND CONTROL EVENTS
OF THREE DIFFERENT RATIOS OF EVENT OCCURRENCES
(THE CHOICE OF AN AVAILABLE EVENT WAS CODED +1.
THE CHOICE OF A CONTROL EVENT WAS CODED -1.)

DISCUSSION

The present study produced three noteworthy findings. First, the availability heuristic was manipulated successfully in a multidimensional task that is characteristic of complex repetitive events in the real world. Results support the general findings that the availability of an event in memory produces an overestimation of the frequency and probability of event occurrences. Choice behavior was similarly affected such that, in binary choice pairs, available events were judged as more likely to occur. Second, the findings draw attention to the importance of event characteristics, for although results supported the overall effect of the availability heuristic, the effect was not consistent across all levels of assigned event frequency. At the middle level of assigned event frequency, the availability heuristic did not create the expected overestimation. This finding was consistent across both frequency and probability estimation and choice predictions. Third, results are not consistent with previous findings of superior performance for frequency estimation over probability estimation (Howell & Kerkar, 1982). The following discussion examines each of these findings in greater detail with an eye toward possible explanations.

Researchers have invoked the availability heuristic as an explanation since its conception by Tversky and Kahneman ten years ago. Unfortunately, the majority of the studies designed to demonstrate the heuristic have employed highly simplistic experimental stimuli which are totally lacking in the "richness" or multidimensionality that

characterizes repetitive events in the real world. Even results from studies which employed "real world" events as stimulus material (Lichtenstein et al., 1978) are to be considered cautiously because the judgments were not based upon actual experience with the data (Shanteau, 1978). Highly simplistic stimuli may not yield simplified representations of real world frequentistic information processing, but rather qualitatively different representations. The judgmental heuristics which mediate the allocation of attention and the resultant activation of special controlled processes when individuals attempt to code, store, and retrieve information cannot be seen in most laboratory investigations because there is rarely any uncertainty about what information should be attended to or how it should be encoded (Marques, Note 2). The findings from the present study demonstrated the generalizability of the effect of the availability heuristic to more complex tasks in which people handle uncertainty intuitively.

The second important finding from the present study suggests that the effect of the availability heuristic may not be the same across all levels of event frequencies. At the middle level of assigned event frequency (12 event occurrences), the availability manipulation did not produce the expected overestimation. In fact, at this level of assigned event frequency subjects judged the occurrences of both available and control events most accurately, while events at the low and high level of frequency were underestimated and overestimated, respectively. The superior accuracy of estimates at the middle frequency range has been demonstrated often in the frequency estimation literature (Erlick, 1964; Stevens & Galanter, 1957; Teigen, 1973). Unfortunately, this literature does not address the availability heuristic and therefore cannot account

for the present reversal at the middle level of assigned event frequency in which the control events were judged to occur reliably more often than the availability events.

One possible explanation for this reversal at the midrange frequency level may be found in the results of a study by Voss, Vereb, and Bisanz (1975). Measuring frequency judgment latencies, these authors discovered an inverted U function of frequency. They suggested that frequency estimation is encoded by different processes, depending upon the assigned frequency of event occurrence. The authors discussed a two-process model of stimulus encoding. The first stage involved a search and counting of stimulus representations for lower frequency values of 2 to 8, whereas the second stage involved access to stimulus encoding and a direct estimate for frequencies of 8 to 32. The suggestion of different processes is an interesting explanation. However, the results of the present study cast doubt on a "counting" explanation for the lower frequency range since the effect of availability appears to be greatest at lower frequency values. Further investigation of the lower to middle range of assigned event frequencies is clearly warranted.

The failure of this study to support the finding (Howell & Kerkar, 1982) that judgments under uncertainty are more accurate under a past-oriented frequency estimation than under a future-oriented probability estimation may appear at first to be contradictory.

Although the procedure of this study closely parallels the general procedures created by Howell and Kerkar (1982), one change in procedure, the availability manipulation, eliminated (or at least greatly reduced) these authors' most consistent finding: superior accuracy of

past-oriented frequency estimations. One explanation might be that the frequency-probability effect is extremely fragile. However, since they observed it under a variety of other task conditions such an account seems unlikely. Rather, the failure of what appears to be a fairly reliable phenomenon under the specific conditions of the present study may provide a clue as to the process by which the availability heuristic operates.

Howell and Kerkar (1982) proposed that in the case of probability estimation the predominant tendency was toward overestimation. They interpreted these findings as consistent with the Howell and Burnett (1978) taxonomy in that probability estimation is seen to depend more heavily on transient information and an "overconfidence" bias. while frequency estimation draws mainly on the (more veridical) stored "frequency record." Extending this line of thought, the present intentional distortion in the encoding of frequentistic information (created by the availability manipulation) may have operated in such a fashion as to distort the frequency record itself (by whatever means it may be represented in memory). To the extent that both estimations are dependent on retrieval of this record, both estimations reflect the distortion. However, to the degree that the frequency estimation is a more direct "readout" of this record, it may be influenced to a greater extent by the availability heuristic. If this is the case, expected superior accuracy of the frequency estimation disappears.

This argument would lead one to believe that judgment for the control events would evidence the superior accuracy of frequency estimation compared with probability estimation. However, the frequency estimates of the control events do not appear to be significantly more

accurate than probability estimates. Due to the fact that the underlying cognitive processes by which the availability heuristic operates have not been delineated, it is impossible to provide more than speculative explanation for these findings. Clearly, the plausibility of such an interpretation awaits further investigation.

In summary, the present study has extended the generalizability of the availability heuristic to more complex tasks in which people judge uncertainty. However, the findings concerning event characteristics and response mode represent only an exploratory step toward defining the degree to which basic findings hold across a range of task characteristics.

REFERENCE NOTES

- Howell, W. C. <u>Task characteristics in the formation and use of uncertainty impressions</u> (Technical Report). Office of Naval Research, November 1981.
- Marques, T. E. Attention-control in the frequentistic processing of multi-dimensional event streams (Technical Report No. 80-13).
 Houston, Tex.: Rice University, August 1980.

REFERENCES

- Anderson, C. A. Abstract and concrete data in the perseverance of social theories: When weak data lead to unshakable beliefs.

 <u>Journal of Experimental Social Psychology</u>, 1983, 19, 93-108.
- Attneave, F. Psychological probability as a function of experienced frequency. Journal of Experimental Psychology, 1953, 46, 81-86.
- Beyth-Marom, R., & Fischhoff, B. Direct measures of availability and judgments of category frequency. <u>Bulletin of Psychonomic Society</u>, 1977, 9, 236-238.
- Crowder, R. G. <u>Principles of learning and memory</u>. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1976.
- Ebbesen, E. B., & Konecni, V. J. On the external validity of decision-making research: What do we know about decisions in the real world? In T. S. Wallsten (Ed.), Cognitive processes in choice and decision behavior. Hillsdale, N.J.: Erlbaum, 1980.
- Edwards, W. Behavioral decision theory. <u>Annual Review of Psychology</u>, 1961, 12, 473-498.
- Edwards, W. Conservatism in human information processing. In B. Kleinmuntz (Ed.), Formal representation of human judgment. New York: Wiley, 1968.
- Edwards, W., & Tversky, A. (Eds.). <u>Decision making</u>. New York: Penguin, 1967.
- Einhorn, H. J., & Hogarth, R. M. Behavioral decision theory: Processes of judgment and choice. <u>Annual Review of Psychology</u>, 1981, 32, 53-88.
- Erlick, D. E. Absolute judgments of discrete quantities randomly distributed over time. <u>Journal of Experimental Psychology</u>, 1964, 67, 475-482.
- Estes, W. K. The cognitive side of probability learning. <u>Psychological</u> <u>Review</u>, 1976, <u>83</u>, 37-64.
- Hammond, K. R. Principles of organization in intuitive and analytical cognition (Report No. 231). Boulder, Col.: University of Colorado, Institute of Behavioral Sciences, Center for Research on Judgment and Policy, February 1981.

- Hammond, K. R., McCelland, G. H., & Mumpower, J. The Colorado report on the integration of approaches to judgment and decision-making (Report No. 211). Boulder, Col.: University of Colorado, Institute of Behavioral Sciences, Center for Research on Judgment and Policy, October 1978.
- Hammond, K. R., McCelland, G. H., & Mumpower, J. <u>Human judgment and decision making: Theories, methods and procedures</u>. New York: Praeger, 1980.
- Hintzman, D. L. Apparent frequency as a frequency and the spacing of repetition. <u>Journal of Experimental Psychology</u>, 1969, 80, 739-745.
- Hintzman, D. L. Repetition and memory. In <u>The psychology of learning</u> and motivation. G. H. Bower (Ed.). New York: Academic Press, 1976.
- Howell, W. C. Compounding uncertainty from internal sources. <u>Journal of Experimental Psychology</u>, 1972, 95(1), 6-13.
- Howell, W. C. Representation of frequency in memory. <u>Psychological</u> <u>Bulletin</u>, 1973, 80, 44-53.
- Howell, W. C., & Burnett, S. A. Uncertainty measurement: A cognitive taxonomy. <u>Organizational Behavior and Human Performance</u>, 1978, <u>22</u>, 45-68.
- Howell, W. C., & Kerkar, S. Uncertainty measurement in a complex task as a function of response mode and event type characteristics.

 Organizational Behavior and Human arformance, 1982, 30, 365-390.
- Kahneman, D., & Tversky, A. Subjective probability: A judgment of representativeness. Cognitive Psychology, 1972, 3, 430-454.
- Kahneman, D., & Tversky, A. Intuitive prediction: Biases and corrective procedures. <u>Cognition</u>, 1979, <u>12</u>, 313-327.
- Lichtenstein, S., & Slovic, P. Reversals of preference between bids and choices in gambling decisions. <u>Journal of Experimental Psychology</u>, 1971, 89, 46-55.
- Lichtenstein, S., & Slovic, P. Response-induced reversal of preference in gambling: An extended replication in Las Vegas. <u>Journal of Experimental Psychology</u>, 1973, 101, 16-20.
- Lichtenstein, S., Slovic, P., Fischhoff, B., Layman, M., & Combs, B. Judged frequency of lethal events. <u>Journal of Experimental Psychology</u>: Human Learning and Memory, 1978, 4, 551-578.
- Miller, F. D. Neighborhood satisfaction among urban dwellers. <u>Journal</u> of Social Issues, 1980, 36, 101-117.

- Nisbett, R. E., & Ross, L. <u>Human inferences: Strategies and shortcomings of social judgment</u>. Englewood Cliffs, N.J.: Prentice-Hall, 1980.
- Pennington, 3. The British fireman's strike in 1977-1978: An investigation of judgments in foresight and hindsight. British Journal of Social Psychology, 1981, 20, 89-96.
- Peterson, C. R., & Beach. L. R. Man as an intuitive statistician. Psychological Bulletin, 1967, 68, 29-46.
- Phelps, R. H., & Shanteau, J. Livestock judges: How much information can an expert use? Organizational Behavior and Human Performance, 1978, 21, 209-219.
- Radtke, R. C., Jacoby, C. L., & Goedel, G. D. Frequency discrimination as a function of frequency of repetition and trials. <u>Journal of Experimental Psychology</u>, 1971, 89, 78-84.
- Rowe, E. J., & Rose, R. J. Effects of orienting task, spacing repetitions and list context on judgments of frequency. Memory and Cognition, 1977, 5, 505-512.
- Saks, M. J., & Kidd, R. F. Human information processing and adjudication--trial by heuristics. <u>Law Sociology Review</u>, 1979, <u>15</u>, 123-160.
- Shanteau, J. When does a response error become a judgmental bias?

 Commentary on "Judged frequency of lethal events." Journal of Experimental Psychology: Human Learning and Memory, 1978, 4, 579-581.
- Slovic, P., Kunreuther, H., & White, G. Decision processes, rationality and adjustment to natural hazards. In G. F. White (Ed.), Natural hazards: Local, national and global. New York: Oxford University Press, 1974.
- Slovic, P., Fischhoff, B., & Lichtenstein, S. Behavioral decision theory. <u>Annual Review of Psychology</u>, 1977, 28, 1-39.
- Slovic, P., & MacPhillamy, D. Dimensional commensurability and cue utilization in comparative judgment. Organizational Behavior and Human Performance, 1974, 11, 172-194.
- Stewens, S. S., & Galanter, E. H. Ratio scales and category scales for a sozen perceptual continua. <u>Journal of Experimental Psychology</u>, 1957, 54, 377-411.
- Taylor, S. E. The availability bias in social perception and interaction In D. Kahneman, P. Slovic, & A. Tversky (Eds.), Judgment under uncertainty: Heuristics and biases. Cambridge: Cambridge University Press, 1982.

- Taylor, S. E., & Thompson, S. C. Stalking the elusive "vividness" effect. <u>Psychological Review</u>, 1982, 89, 155-182.
- Teigen, K. H. Number and percentage estimates in sequential tasks.

 <u>Perceptual and Motor Skills</u>, 1973, 36, 1035-1038.
- Tversky, A., & Kahneman, D. Belief in the law of small numbers. Psychological Bulletin, 1971, 76, 105-110.
- Tversky, A., & Kahneman, D. Availability: A heuristic for judging frequency and probability. <u>Cognitive Psychology</u>, 1973, 5, 207-232.
- Tversky, A., & Kahneman, D. Judgment under uncertainty: Heuristic and biases. Science, 1974, 185, 1124-1131.
- Tversky, A., & Kahneman, D. The framing of decisions and the psychology of choice. <u>Science</u>, 1981, <u>211</u>, 453-458.
- Tversky, A., & Kahneman, D. Availability: A heuristic for judging frequency and probability. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), Judgment under uncertainty: Heuristics and biases. Cambridge: Cambridge University Press, 1982.
- Underwood, B. J. Attributes of memory. <u>Psychological Review</u>, 1969, <u>76</u>, 559-573.
- Underwood, B. J., Zimmerman, J., & Freund, J. S. Retention of frequency information with observations on recognition and recall. <u>Journal</u> of Experimental Psychology, 1971, 87, 149-162.
- Voss, J. L., Vereb, C., & Bisanz, G. Stimulus frequency judgments and latency of stimulus frequency judgments as a function of constant and variable response conditions. <u>Journal of Experimental</u> Psychology: Human Learning and Memory, 1975, 1, 337-350.
- Whitlow, J. W., & Skaar, E. The role of numerosity in judgments of overall frequency. <u>Journal of Experimental Psychology: Human Learning and Memory</u>, 1979, 5, 409-421.

APPENDIX A EXPERIMENTAL QUESTIONNAIRES

FREQUENCY ESTIMATIONS

Please base your estimations on the $\underline{\text{total}}$ number of events that you experienced over all three sessions.

1.	How many	total	police	calls	did	you	receive?	
2.	How many	total	ambular	nce cal	lls d	lid v	vou receive?	

3.	Using the	grid presented below, indicate number of police a	ind
	ambulance	calls you received in each district.	

1	2	3
Police Ambulance	Police Ambulance	Police Ambulance
4	5	6
Police Ambulance	Police Ambulance	Police Ambulance
7	8	9
Police Ambulance	Police Ambulance	Police Ambulance

PROBABILITY ESTIMATIONS

Please base your estimates on the <u>total</u> number of events that you experienced over all three sessions.

- 1. If a call comes in, what are the chances (0-100%) that it is a police call?
- 2. If a call comes in, what are the chances (0-100%) that it is an ambulance call?
- 3. Using the grid below, estimate the chance as a percentage (0-100%) that police and ambulance calls will occur in each district.

1	2	3
Police Ambulance	Police Ambulance	% % Police Ambulance
4	5	6
% % Police Ambulance	% % Police Ambulance	% % Police Ambulance
7	8	9
Police Ambulance	Police Ambulance	% % Police Ambulance

CHOICE PREDICTIONS

The following is a list of pairs of events. P stands for police. A stands for ambulance. The number that follows indicates the district in which the event occurred. Please circle which of the events in each pair is more likely to occur. Feel free to use your map as a reference at any time.

A2	P5	A5	P5
A2	P8	P8	P6
P5	А9	A4	P8
A4	P4	A5	P8
A4	P5	A4	A2
A4	А9	A2	P4
A2	Р9	A4	A5
P6	P5	A5	P9
A9	A5	P6	A9
A5	P6	P9	A4
A5	P4	A9	Р8
P4	P8	P4	A9
A2	А9	P5	Р9
Р9	A9	P6	A4
P4	P5	Р9	P8
P6	Р9	P6	P4
A2	P6		

APPENDIX B EXAMPLES OF CASE HISTORIES

Example 1

Can you send an ambulance to the 6th Ward neighborhood pool? We've got a kid who has just been pulled out from the bottom of the deep end. No one knows how long he was down there. Three lifeguards are working on him now. It looks bad, please hurry.

A4 Residential-Low Income

Example 2

Something terrible has happened!
My son came home this morning around
4:00 a.m. He had blood all over his
clothes. He took them in the back
yard and burned them. He's carrying
a gun with him. Please do something
before he hurts himself or someone
else.

P6 Residential-Middle Income

APPENDIX C FIGURES

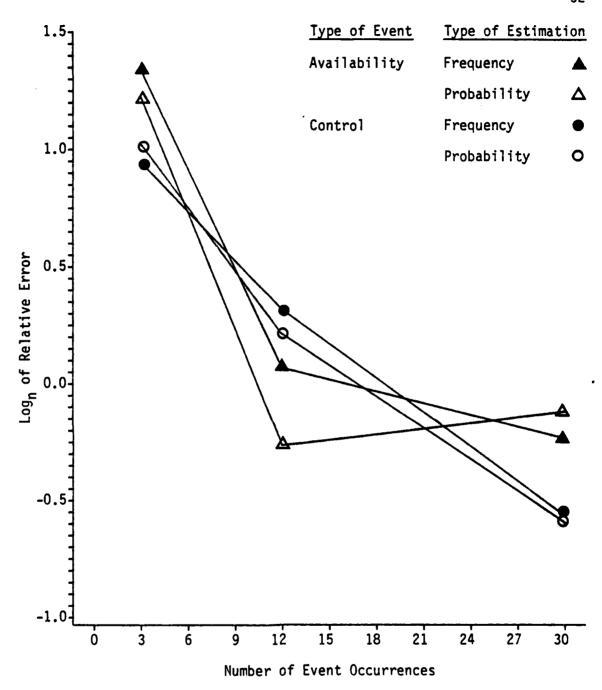


FIGURE A

LOG TRANSFORMATION OF RELATIVE ERROR
CALCULATED WITH THE ADJUSTED ESTIMATION
FOR FREQUENCY AND PROBABILITY ESTIMATION PERFORMANCE
FOR TYPE OF EVENT (AVAILABILITY VERSUS CONTROL)
AND LEVEL OF EVENT OCCURRENCES (3 VERSUS 12 VERSUS 30)

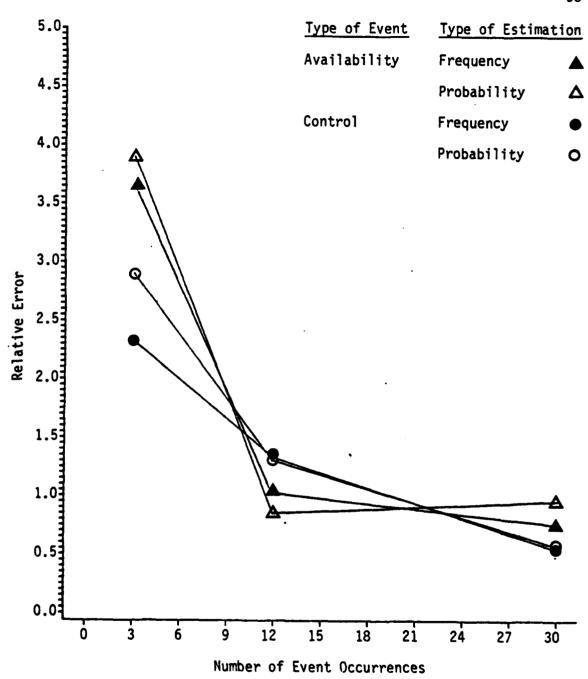


FIGURE B

RELATIVE ERROR FOR FREQUENCY AND PROBABILITY ESTIMATION PERFORMANCE FOR TYPE OF EVENT (AVAILABILITY VERSUS CONTROL)
AND LEVEL OF OCCURRENCE (3 VERSUS 12 VERSUS 30)

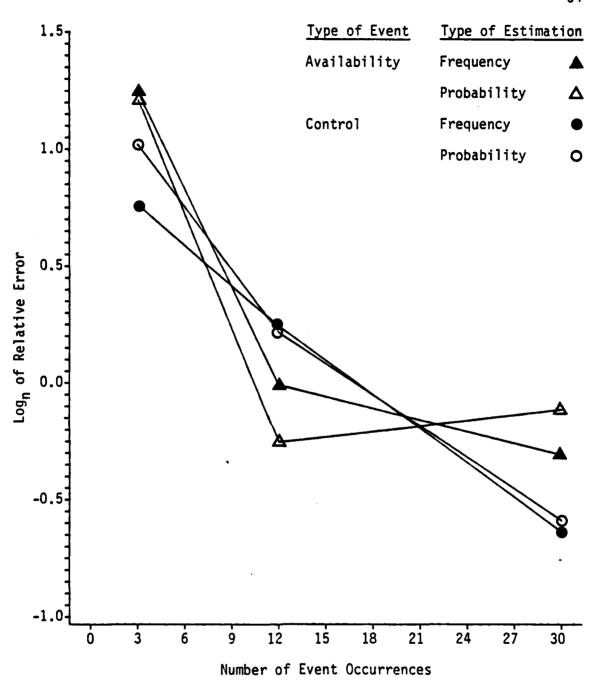


FIGURE C
LOG TRANSFORMATION OF RELATIVE ERROR

FOR FREQUENCY AND PROBABILITY ESTIMATIONS
FOR TYPE OF EVENT (AVAILABILITY VERSUS CONTROL)
AND LEVEL OF OCCURRENCE (3 VERSUS 12 VERSUS 30)

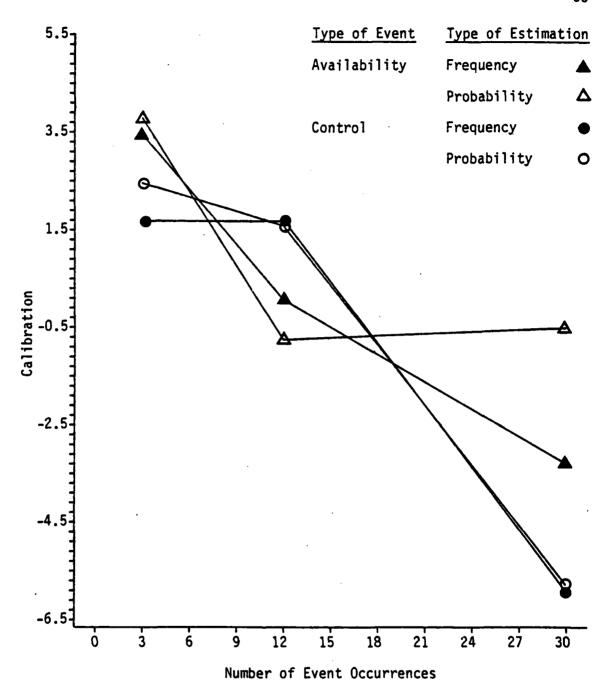


FIGURE D

CALIBRATION (SIGNED ERROR) FOR FREQUENCY AND PROBABILITY ESTIMATINOS
FOR TYPE OF EVENT (AVAILABILITY VERSUS CONTROL)
AND LEVEL OF OCCURRENCE (3 VERSUS 12 VERSUS 30)

APPENDIX D
ANALYSIS OF VARIANCE TABLES

TABLE A

ANALYSIS OF VARIANCE TABLE OF RELATIVE ERROR

CALCULATED WITH THE ADJUSTED ESTIMATE FOR FREQUENCY AND PROBABILITY ESTIMATIONS

	Sum of Squares	Degrees of Freedom	Mean Square	╙Ӏ	<u>п</u> -(p Ê-corrected p
Mean	591.87	, 1	59.187	880.37	000.	
Type of Estimation (Frequency versus Probability)	.02	1	.02	.02	.881	
Error	20.17	30	.67			
Type of Event (Available versus Control)	5.64		5.64	69.6	.004	
Event by Estimation	.05	-	.05	.08	.782	
Error	17.45	30	.58			
Number of Occurrences	258.14	2	129.07	214.18	000	0.
Occurrences by Estimation	ż.	7	.27	.45	.639	.54
Error	36.16	09	.60			
Event by Occurrences	17.57	2	8.78	12.23	000	.001
Event by Occurrences by Estimation	.31	7	.16	.22	.81	.67
Error	43.15	09	.71			

TABLE B

ANALYSIS OF VARIANCE TABLE OF THE LOG TRANSFORMATION OF RELATIVE ERROR

CALCULATED WITH THE ADJUSTED ESTIMATE FOR FREQUENCY AND PROBABILITY ESTIMATIONS

	Sum of Squares	Sum of Degrees of Squares Freedom	Mean Square	ഥ	p Ê-corrected p	rected p
Mean	14.68	7	14.68	176.7	000.	
Type of Estimation (Frequency versus Probability)	.18		.18	2.1	.154	
Error	2.49	30	.08			
Type of Event (Available versus Control)	.60	pared.	.60	6.20	.019	
Event by Estimation	.10	-4	.10	1.04	.32	
Error	2.90	30	.10			
Number of Occurrences	76.30	2	38.15	301.89	. 000	0.
Occurrences by Estimation	.58	2	.29	2.30	.108	.11
Error	7.58	09	.13			
Event by Occurrences	5.51	2	2.75	17.54	000.	000.
Event by Occurrences by Estimation	.33	2	.16	1.05	. 35	.34
Error	9.45	09	.16			·

ANALYSIS OF VARIANCE TABLE OF RELATIVE ERROR OF FREQUENCY AND PROBABILITY ESTIMATIONS TABLE C

	Sum of Squares	Sum of Degrees of Squares Freedom	Mean	1 -1	ᅄ	Ê-corrected p
Mean	538.61	1	538.61	905.28	000.	
Type of Estimation (Frequency versus Probability)	1.04	-	1.04	1.74	.197	
Error	17.85	30	.59			
Type of Event (Available versus Control)	6.52		6.52	10.10	.003	
Event by Estimation	.14	-	.14	.21	.651	
Error	19.36	30	.65			
Number of Occurrences	228.03	2	114.02	258.79	000.	000.
Occurrences by Estimation	1.98	2	66.	2.25	.114	.138
Error	20.43	09	44.			
Event by Occurrences	19.70	2	9.34	13.17	000.	.001
Event by Occurrences by Estimation	.63	2	.32	.42	.657	.541
Error	44.86	09	.75			

TABLE D

ANALYSIS OF VARIANCE TABLE OF THE LOG TRANSFORMATION OF RELATIVE ERROR

FOR FREQUENCY AND PROBABILITY ESTIMATIONS

	Sum of Squares	Degrees of Freedom	Mean Square	ഥ	리	p E-corrected p
Mean	66.6	1	66.6	90.69	000	
Type of Estimation (Frequency versus Probability)	90.	1	90.	.45	.509	
Error	4.34	30	.14			
Type of Event (Available versus Control)	.82		.82	7.16	.012	
Event by Estimation	.19		.19	1.63	.21	
Error	3.42	30	.11			
Number of Occurrences	73.56	2	36.78	304.17	000	000.
Occurrences by Estimation	.68	2	.34	2.79	690.	.072
Error	7.26	09	.12			
Event by Occurrences	5.85	2	2.91	17.96	000.	000
Event by Occurrences by Estimation	.45	2	.22	1.38	.259	.259
Error	9.72	09	.16			

TABLE E
ANALYSIS OF VARIANCE TABLE OF CALIBRATION (SIGNED ERROR)
FOR FREQUENCY AND PROBABILITY ESTIMATIONS

	Sum of Squares	Sum of Degrees of	Mean Square	ഥ	ᆈ	<u>E-corrected p</u>
Mean	3.78	1	3.78	.59	.450	
Type of Estimation (Frequency versus Probability)	13.61	1	13.61	2.11	.156	
Error	193.12	30	6.44			
Type of Event (Available versus Control)	66.13	1	66.13	12.67	.001	
Event by Estimation	2.32		2.32	.45	.510	
Error	156.54	30	5.22			
Number of Occurrences	1533.66	2	766.83	139.34	000	0.
Occurrences by Estimation	30.35	2	15.17	2.76	.072	60°
Error	330.20	09	5.50			
Event by Occurrences	291.78	2	145.89	27.11	000.	000.
Event by Occurrences by Estimation	27.39	2	13.70	2.55	.087	680.
Error	322.90	09	5.38			

TABLE F

ANALYSIS OF VARIANCE TABLE FOR PREDICTIVE CHOICE PERFORMANCE COMPARING AVAILABLE AND CONTROL EVENTS OF IDENTICAL FREQUENCY

	Squares	Squares Freedom	Mean	u-1	d U	p E-corrected p
Mean	7.51		7.51	4.41	.045	
Type of Estimation (Frequency versus Probability)	2.18	-	2.17	1.28	.268	
Error	47.64	28	1.70			
Ratio of Occurrences	56.09	2	28.04	12.24	000.	000.
Occurrences by Estimation	2.22	2	1.11	.48	.618	.618
Error	128.36	26	2.29			

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